Networked iterative learning fault Diagnosis algorithm for systems with sensor random packet losses, time-varying delays, limited communication and actuator failure : Application to the hydroturbine Governing System

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Abstract: An iterative learning fault diagnosis (ILFD) algorithm for networked control systems (NCSs) subject to random packet losses, time-varying delays, limited communication and actuator failure is proposed in this paper. Firstly, in order to evaluate the effect of fault on system between every iteration, the information of state error and information of fault tracking estimator from the preceding iteration are used to improve the fault estimation achievement in the actual iteration. The state variable, the Bernoulli process of random packet losses, network communication delay, limited communication and actuator failure are introduced to establish an extended state-space model of the system. Secondly combining Lyapunov stability theory for linear repetitive processes and linear matrix inequality (LMI) technique, new sufficient condition for the existence of an iterative learning fault diagnosis is established. Finally, the feasibility and effectiveness of the proposed design method is illustrated on a dynamic hydroturbine governing system model based on Matlab/Simulink and TrueTime toolbox.

Key-Words: Iterative learning , fault diagnosis, networked control systems , packet losses, limited communication, hydroturbine governing system

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1 Introduction

Modern operation in the hydro power production industry is aimed oriented to remote control and monitoring. The constantly evolving economic challenges lead to produce always more. The least failure on an industrial process is harmful in an environment where performance is essential. It is therefore necessary to be ensured permanently of the optimal control of process. Information making it possible to translate the behaviour of a system is given by measurements of the variables of this process. The quality of measurements is an essential element to allow the monitoring and the performance evaluation of a process. The growing complexity of industrial systems which became increasingly demanding in terms of reliability, performances, safety constraint and availabilities has given rise to growing interest in fault tolerant control and diagnostics [1, 2, 3, 4].

The challenge of fault diagnosis has been studied widely in the literature [5, 6, 7, 8, 9, 10, 11]. The major part of research was devoted to the problem of fault detection and isolation so as to determine the operating condition of the system (normal or failing). Several approaches and methods are used to solve this problem: H_∞ fault detection filter [6, 7, 10, 13], Sliding mode methods for fault detection [10, 11], adaptive fault detection filter [10, 12] , fuzzy inference systems and artificial neural network based fault diagnosis [10, 14, 15]. However, majority industrial processes are repetitive systems [16, 17, 18], learning knowledge and operation upon the preceding iteration are ignored in traditional fault detection approaches above-mentioned. Nevertheless, with the development of information treatment technology, huge research efforts have been dedicated to development of a fault estimation by utilizing neural network methods [14, 15] and iterative learning approaches [19, 20, 21]. Overall, the methods of neural network have been accomplished for complex systems, moreover the model of the system is not available.

Nonetheless, Based on fault estimation challenges on a perfect system, an iterative learning technique is a more viable track. A fault tracking estimate and an iterative learning algorithm have been used to get fault estimates functions for systems with time-delay in [22]. Moreover in [23] , an iterative learning observer is developed by utilizing preceding yield estimation errors and inputs. Inspired by the preliminary review, this paper presents a Networked iterative learning Fault Diagnosis algorithm for systems with sensor random packet losses, time-varying delays, limited communication and actuator faults. Furthermore, it is supposed that information transmission and reception bare made through the communication medium with capacity constraint, random packet losses exists in sensor-controller links , it is designed as a Bernoulli process and actuator faults in a same pattern. Moreover, the actuator fault includes the proceedings of failure and stuck fault. Thus, this work proposes an approach of synthesis of an iterative learning observer to estimate the exact information of fault.

The main contributions of this paper are highlighted as follows:

- the actuator fault estimation problem is extended for a class of networked control systems (NCSs) with random packet losses, time-varying delays and limited communication; employing the Lyapunov stability theory, new sufficient conditions are established to guarantee the iterative tracking error trial to trial convergence.
- Application to a Hydro-turbine governing system shows that the proposed iterative learning algorithm achieves better fault estimation.

  True-Time toolbox is used to reflect a more realistic numerical network communication and validity of the proposed design method is illustrated on the model of hydroturbine governing system [24].

The rest of this paper is organized as follows: section 2 introduces the problem statement and preliminaries, our step of fault estimation using an iterative learning scheme is proposed to achieve desired fault estimation results and the sufficient conditions which make the considered system to be asymptotically stable and meet is given in section 3. The simulation results based on True-Time toolbox and Matlab/Simulink will be given in section 4 to verify the efficiency of proposed method. Finally, the paper is concluded in section 5.

2 Problem Formulation

In this paper, the linear output sampling system with time-varying, packet losses, limited communication and actuator fault is considered. State-space model of the dynamic process can be described by the following form:

$$\begin{aligned} x_k(t+1) &= Ax_k(t) + A_\tau x_k(t-\tau(t)), \\ &\quad +Bu_k^F(t) \\ y_k(t) &= Cx_k(t),\; x_k(0) = x_0,\; 0 \leq t \leq \mathrm{T_c} \end{aligned} \tag{1}$$

where k denotes the iteration index, $k \geq 0$, t is the time index, $\mathrm{T_c}$ is the iteration length ; $x_k(t) \in R^n$, $u_k(t) \in R^p$ are the system state vector, control input vector, x_0 denotes the initial state. $x_k(t) \in R^n$ and $y_k(t) \in R^p$ are system state vector and output vector at discrete time t respectively, $u_k^F(t)$ denotes the actual output of the possible faulty actuator, $d_k(t) \in R^q$ is the disturbance in the system, τ is is the discrete time-varying communication delays such as $\tau \in [\tau_m, \tau_M]$; τ_m and τ_M are constant positive scalars representing the lower and upper bounds). A, B, C, and A_τ are constant matrices with appropriate dimensions.

The boundary conditions $x_k(0) = x_0$ represent the initial condition of the system at the t time.

In a similar way to [25], the actuator fault model used in this paper is described as follows

$$u_k^F(t) = \lambda u_k(t) + \alpha u_k^f(t) \tag{2}$$

where

$$u_k^f(t) = \begin{bmatrix} u_k^{f,1}(t) & u_k^{f,2}(t) & \cdots & u_k^{f,m}(t) \end{bmatrix}^T \tag{3}$$

$$\lambda \in \{\ \lambda^1,\ \ \lambda^2,\ \ \cdots\ \ \lambda^l\ \} \tag{4}$$

$$\alpha \in \{\ \alpha^1,\ \ \alpha^2,\ \ \cdots\ \ \alpha^l\ \} \tag{5}$$

In which, l denotes the total faulty modes, λ and α are the time-varying diagonal matrix of efficiency actuator factor and

$$\lambda^j \in \begin{bmatrix} \lambda_1^j & 0 & \cdots & 0 \\ 0 & \lambda_2^j & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_m^j \end{bmatrix} \tag{6}$$

$$\alpha^j \in \begin{bmatrix} \alpha_1^j & 0 & \cdots & 0 \\ 0 & \alpha_2^j & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha_m^j \end{bmatrix} \tag{7}$$

with

$\lambda_i^j \in [\ \bar{\lambda}_i,\ \ \underline{\lambda}_i\ ], \alpha_i^j = 0$ or 1.

Hence, we establish

$$\underline{\lambda} = \begin{bmatrix} \underline{\lambda}_1 & 0 & \cdots & 0 \\ 0 & \underline{\lambda}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \underline{\lambda}_m \end{bmatrix}, \tag{8}$$

$$\bar{\lambda} = \begin{bmatrix} \bar{\lambda}_1 & 0 & \cdots & 0 \\ 0 & \bar{\lambda}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \bar{\lambda}_m \end{bmatrix}, \tag{9}$$

Table 1. present the possible actuator failure considered in this paper.
If we denote by $\tilde{u}_k(t)$ the control signals generated

Table 1: Actuator failure cases.

Case	Actuator failure
$\lambda^j = 1$, α^j=0	Actuator is normal
$\lambda^j = 0$, $\alpha^j = 0$	Actuator is outage
$\lambda^j = 0$, $\alpha^j = 1$	Actuator is stuck fault

by controller at discrete time t. Based on the above communication sequence, the control input signal is expressed as:

$$\tilde{u}_k(t) = M_\varrho(t).u_k^{\mathcal{F}}(t) \tag{10}$$

. where

$$M_\varrho = \begin{bmatrix} \varrho_1(t) & 0 & \cdots & 0 \\ 0 & \varrho_2(t) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \varrho_3(t) \end{bmatrix},$$

and
$\varrho_i(t) \in \{0, 1\}, \sum_{i=1}^{m} \varrho_i(t) \leq m.$

It is suppose that random packet losses exist in Sensors to controller link.
The following equations describe this phenomena [26]:

$$\bar{y}_k(t) = \beta_k(t)y_k(t) + (1 - \beta_k(t))\bar{y}_{k-1}(t) \tag{11}$$

where $\beta_k(t)$ is a stochastic variable which satisfies Bernoulli distribution with

$$Pr\{\beta_k(t) = 1\} = E\{\beta_k(t)\} = \bar{\beta}, \tag{12}$$

where
$0 \leq \bar{\beta} \leq 1$

If $\beta_k(t) = 0$, it assumes that the packet $\bar{y}_k(t)$ is lost, and the data of $\bar{y}_{k-1}(t)$ would be used in the system.
Substituting the fault matrix (2),(10) and (11), the dynamic of augmented model such as illustrated in fig 1 may be obtained:

$$\begin{aligned} x_k(t+1) = Ax_k(t) + A_\tau x_k(t - \tau(t)) \\ +B\lambda M_\varrho(t)u_k(t) + \alpha B \\ \times M_\varrho(t)u_k^f(t) \end{aligned} \tag{13}$$

$$\begin{aligned} \tilde{y}_k(t) = \beta_k(t)Cx_k(t) + (1 - \beta(t)) \\ \times C\tilde{y}_{k-1}(t) \end{aligned}$$

To end this section, we introduce the following lemmas which will be used there after.

Lemma 1 *([27]). Given matrices $T = T^T$, X, Y, B of appropriate dimensions, then:*

- $T + XBY + Y^T B^T X^T < 0$

for all B satisfying $B^T B \leq I$, if there exists a scalar $\upsilon > 0$ such that:

- $T + \upsilon XX^T + \upsilon^{-1}Y^T Y < 0$

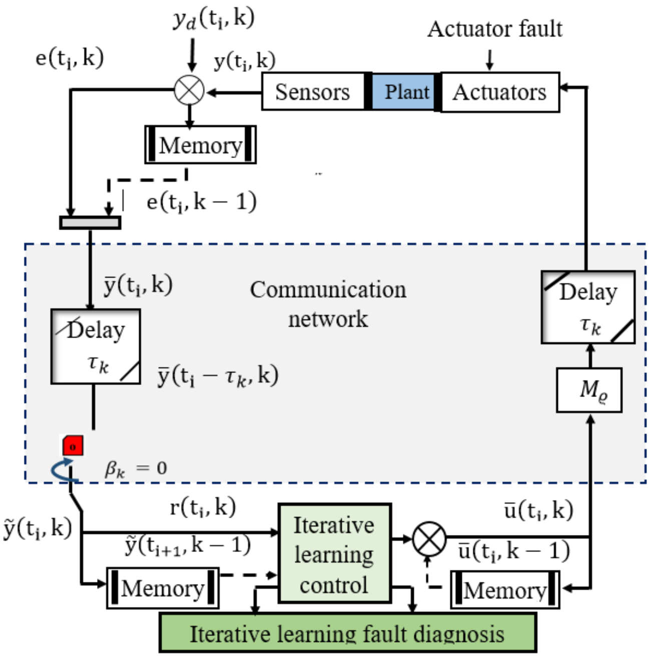

Figure 1: The proposed block diagram of networked iterative learning fault diagnosis systems with sensor random packet losses, time-varying delays and limited communication.

Lemma 2 *([28]) Given constant matrices of compatible dimensions Σ_{11},*
$Sigma_{12}$ and $\Sigma_{22} \in R^{n \times n}$, where $\Sigma_{11} = \Sigma_{11}^T$ and $\Sigma_{22} = \Sigma_{22}^T$; the following conditions are equivalent:

1 $\begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{12}^T & \Sigma_{22} \end{bmatrix} < 0$

2 $\Sigma_{11} < 0, \Sigma_{22} - \Sigma_{12}^T \Sigma_{11}^{-1} \Sigma_{12} < 0$

3 $\Sigma_{22} < 0, \Sigma_{11} - \Sigma_{12}^T \Sigma_{22}^{-1} \Sigma_{12} < 0$

where the symbols $(*)$ denote the symmetric terms.

3 Iterative learning observer design

According to (13), the observer based fault detection for the system is developed as follows

$$\begin{array}{c}\hat{x}_k(t+1) = A\hat{x}_k(t) + A_\tau\hat{x}_k(t-\tau(t)),\\ +B\lambda M_\varrho(t)u_k(t)\\ +\alpha BM_\varrho(t)\hat{u}^f_k(t)\\ +L\left[\tilde{y}_k(t) - \hat{y}_k(t)\right]\end{array} \tag{14}$$

$$\begin{array}{c}\hat{y}_k(t) = \beta_k(t)\,C\hat{x}_k(t) + (1-\beta(t))\\ \times C\hat{y}_{k-1}(t)\end{array} \tag{15}$$

Where $\hat{x}_k(t)$ m and $\hat{y}_k(t)$, $\hat{u}^f_k(t)$ denote the state estimate of the system, the estimate of the output vector and estimate of fault signal at k iterations learning respectively , L is the matrix gain observer.
We define $\varepsilon_k(t)$ the estimation error in the k^{th} trial as

$$\varepsilon_k(t) = x_k(t) - \hat{x}_k(t) \tag{16}$$

the output error by

$$\bar{r}_k(t) = y_k(t) - \hat{y}_k(t) \tag{17}$$

and the fault estimation error by

$$\breve{u}^f_k(t) = u^f_k(t) - \hat{u}^f_k(t) \tag{18}$$

According to (13)-(16), the expression of the dynamic error $\varepsilon_k(t)$ is obtained as

$$\begin{array}{c}\varepsilon_k(t+1) = \left[A + L\beta(t)\,C\right]\varepsilon_k(t)\\ +A_\tau\varepsilon_k(t-\tau(t)) + \alpha BM_\varrho(t)\eta_k(t)\\ +(1-\beta(t))r_k(t-1)\end{array} \tag{19}$$

Thus, the following iterative learning based fault estimation is proposed as

$$\begin{array}{c}\hat{u}^f_k(t+1) = \hat{u}^f_k(t) + \Lambda_1 e_k(t)\\ +\Lambda_2 e_k(t+1)\end{array} \tag{20}$$

where Λ_1 and Λ_2 are consistently dimensioned matrices gain fault to be conceived.
For the purpose of facilitate the following expressions, It can denote the error of iterative learning fault estimation as

$$\begin{array}{c}\varepsilon_k(t+1) = \bar{A}_1\varepsilon_k(t) + A_\tau\varepsilon_k(t-\tau(t))\\ +\bar{B}_1\eta_k(t) + \bar{C}_1 r_k(t-1)\end{array} \tag{21}$$

$$\begin{array}{c}\eta_k(t+1) = \eta_k(t) + \bar{A}_2\varepsilon_k(t)\\ +\Lambda_2 A_\tau\varepsilon_k(t-\tau(t))\\ +\bar{B}_2\eta_k(t) + \bar{C}_2 r_k(t-1)\end{array} \tag{22}$$

where
$\bar{A}_1 = A + L\beta(t)\,C$
$\bar{B}_1 = \alpha BM_\varrho(t)$
$\bar{C}_1 = (1-\beta(t))I$
$\bar{A}_2 = \Lambda_1 + \Lambda_2\left(A + L\beta(t)\,C\right)$
$\bar{B}_2 = \alpha\Lambda_2 BM_\varrho(t)$
$\bar{C}_2 = \Lambda_2(1-\beta(t))$.

Denote extended vectors:

$$\bar{\varepsilon}_k(t) = \left[\begin{array}{cc}\varepsilon_k(t) & \varepsilon_k(t-\tau(t)\end{array}\right]^T$$

$$\bar{\eta}_k(t) = \left[\begin{array}{cc}\eta_k(t) & r_k(t-1)\end{array}\right]^T$$

According to (21) and (22), the following equation can be obtained

$$\begin{array}{c}\bar{\varepsilon}_k(t+1) = \Pi_1\bar{\varepsilon}_k(t) + \Pi_2\bar{\eta}_k(t)\\ \bar{\eta}_k(t+1) = \Pi_3\bar{\varepsilon}_k(t) + \Pi_4\bar{\eta}_k(t),\end{array} \tag{23}$$

where

$$\Pi_1 = \left[\begin{array}{cc}\bar{A}_1 & A_\tau\\ \bar{A}_2 & \Lambda_2 A_\tau\end{array}\right],$$
$$\Pi_2 = \left[\begin{array}{cc}\bar{B}_1 & \bar{C}_1\\ I+\bar{B}_2 & \bar{C}_2\end{array}\right],$$
$$\Pi_3 = \left[\begin{array}{cc}\bar{A}_2 & \Lambda_2 A_\tau\\ \beta(t)C & 0\end{array}\right],$$
$$\Pi_4 = \left[\begin{array}{cc}I+\bar{B}_2 & \bar{C}_2\\ 0 & (1-\beta(t))I\end{array}\right],$$

Theorem 1 *.The ILFDS system (23) at k iteration is stable along the elapse it if exists a scalar $\zeta > 0$ and positive matrices $\bar{P}_1 > 0$, $\bar{Q}_1 > 0$, $\bar{P}_2$ and $\bar{Q}_2$ such that the following LMI holds:*

$$\left[\begin{array}{ccccc}-\bar{P}_1^{-1} & * & * & * & *\\ 0 & -\bar{Q}_1^{-1} & * & * & *\\ \bar{P}_1^{-1}\Pi_1 & \bar{P}_2^{-1}\Pi_{21} & \bar{\Pi}_{33} & * & *\\ \bar{P}^{-1}\Pi_3 & \bar{\Pi}_{41} & -\zeta I & \bar{\Pi}_{44} & *\\ \bar{P}_2 & \bar{Q}_2 & 0 & 0 & -\zeta I\end{array}\right] < 0$$
(24)

where
$\bar{\Pi}_{33} = -\bar{P}_1^{-1} + \zeta I$
$\bar{\Pi}_{44} = -\bar{Q}^{-1} - \zeta I$

If this LMI holds, the fault matrices gains Λ_1 and Λ_2 can be determined on the basis

$$\begin{array}{c}\Lambda_1 = \bar{P}_2\bar{P}_1\\ \Lambda_2 = \bar{Q}_2\bar{Q}_1\end{array} \tag{25}$$

Proof 1 *. we select the Lyapunov function in the following way*

$$V_k(t) = \bar{e}_k^T(t)\bar{P}_1\bar{e}_k(t) + \bar{\eta}_k^T(t)\bar{Q}_1\bar{\eta}_k(t)(t) \tag{26}$$

$$\begin{array}{c}\Delta V_k(t) = \bar{e}_k^T(t+1)\bar{P}_1\bar{e}_k^T(t+1)\\ +\bar{e}_k^T(t)\bar{P}_1\bar{e}_k(t) + \bar{\eta}_k^T(t+1)\bar{Q}_1\bar{\eta}_k(t+1)\\ -\bar{\eta}_k^T(t)\bar{Q}_1\bar{\eta}_k(t)\end{array} \tag{27}$$

$$\Delta V_k(t) = \begin{bmatrix} \bar{e}_k^T(t+1) & \bar{\eta}_k^T(t) \end{bmatrix} \times \left(\bar{\Pi}^T D \bar{\Pi} - D\right) \begin{bmatrix} \bar{e}_k^T(t+1) \\ \bar{\eta}_k^T(t) \end{bmatrix} \quad (28)$$

where

$$\bar{\Pi} = \begin{bmatrix} \Pi_1 & \Pi_2 \\ \Pi_3 & \Pi_4 \end{bmatrix}, D = diag\{ \bar{P}_1 \quad \bar{Q}_1 \},$$

Therefore, (23) is stable along the elapse it if exists $D > 0$ so that

$$\bar{\Pi}^T D \bar{\Pi} - D < 0 \quad (29)$$

Applying Schurs complement to (29) yields

$$\begin{bmatrix} -\bar{P}_1^{-1} & * & * & * \\ 0 & -\bar{Q}_1^{-1} & * & * \\ \Pi_1 & \Pi_2 & -\bar{P}_1^{-1} & * \\ \Pi_3 & \Pi_4 & 0 & -\bar{Q}_1^{-1} \end{bmatrix} < 0 \quad (30)$$

the multiplication of inequality (30) by left and right side by $diag\left\{ \bar{P}_1^{-1} \quad \bar{Q}_1^{-1} \quad I \quad I \right\}$ to get

$$\begin{bmatrix} -\bar{P}_1^{-1} & * & * & * \\ 0 & -\bar{Q}_1^{-1} & * & * \\ \bar{P}_1^{-1}\Pi_1 & \bar{P}_1^{-1}\Pi_2 & -\bar{P}_1^{-1} & * \\ \bar{P}_1^{-1}\Pi_3 & \bar{P}_1^{-1}\Pi_4 & 0 & -\bar{Q}_1^{-1} \end{bmatrix} < 0$$

(31)

Moreover

$$\Xi_1 + \Xi_2 \alpha \Xi_3 + \Xi_3^T \alpha^T \Xi_2^T < 0 \quad (32)$$

where

$$\Xi_1 = \begin{bmatrix} -\bar{P}_1 & * & * & * \\ 0 & -\bar{Q}_1 & * & * \\ \bar{P}_1^{-1}\Pi_1 & \bar{P}_1^{-1}\bar{\Pi}_{21} & -\bar{P}_1^{-1} & * \\ \bar{P}_1^{-1}\Pi_3 & \bar{\Pi}_{41} & 0 & -\bar{Q}_1^{-1} \end{bmatrix},$$

$$\Xi_2 = \begin{bmatrix} 0 & 0 & I & I \end{bmatrix}^T,$$

$$\Xi_3 = \begin{bmatrix} \bar{\Pi}_{22}\bar{P}_1^{-1} & \bar{\Pi}_{42}\bar{Q}_1^{-1} & 0 & 0 \end{bmatrix},$$

$$\bar{\Pi}_{21} = \begin{bmatrix} \alpha B M_{\varrho k} & \bar{C}_1 \\ I & \bar{C}_2 \end{bmatrix},$$

$$\bar{\Pi}_{22} = \begin{bmatrix} M_{\varrho k} & 0 \\ \Lambda_2 M_{\varrho k} & 0 \end{bmatrix},$$

$$\bar{\Pi}_{41} = \begin{bmatrix} I & \bar{C}_2 \\ 0 & (1-\beta(t))I \end{bmatrix},$$

$$\bar{\Pi}_{42} = \begin{bmatrix} M_{\varrho k} & 0 \\ 0 & 0 \end{bmatrix},$$

According to Lemma(1), as a result (29) holds if it exists a scalar ζ>0 so that

$$\Xi_1 + \zeta \Xi_2 \alpha \Sigma_0 \Xi_2^T + \zeta^{-1} \Xi_3 \Xi_3^T < 0 \quad (33)$$

Applying Schurs complement to (31), following equation can be obtained

$$\begin{bmatrix} \Xi_1 + \zeta \Xi_2 \alpha \Xi_2^T & * \\ \Xi_3 & -\zeta I \end{bmatrix} < 0 \quad (34)$$

Finally, introducing the following equations

$$\bar{P}_2 = \Lambda_1 \bar{P}_1^{-1}, \quad \bar{Q}_2 = \Lambda_2 \bar{Q}_1^{-1} \quad (35)$$

the proof is complete.

4 Simulation Results

In this section, we propose a numerical example of simulation to illustrate the effectiveness of ILFD algorithm presented in this work.
We consider the model of networked control hydro-electric power plant given in [24]. The flowchart of winnowing device control and communication network is represented on Fig 6.

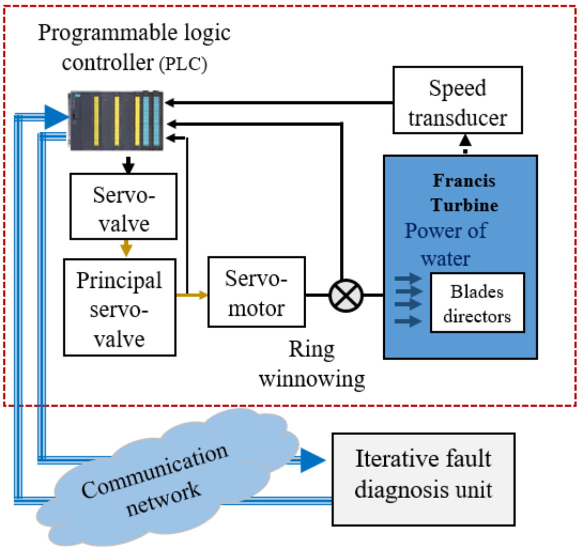

Figure 2: Schematic diagram of networked control hydro turbine governor system.

The state space representation of dynamic model with actuator fault may be presented as follows :

$$\begin{aligned} x_k(t+1) &= A x_k(t) + B u_k^F(t) \\ &+ A_\tau x_k(t-\tau(t)) + \Gamma d(t) \\ y_k(t) &= C x_k(t) \end{aligned} \quad (36)$$

The parameters are given as follows by

$$A = \begin{bmatrix} 1.1840 & -0.4046 & 0 \\ 0.5000 & 0 & 0 \\ 0 & 0.5000 & 0 \end{bmatrix}, B = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix},$$

$C = \begin{bmatrix} 0.2943 & 0.3382 & 0.0001 \end{bmatrix}$ and

$$A_{\tau_k} = \begin{bmatrix} 0.034 & 0 & -0.01 \\ 0.031 & 0.03 & 0 \\ 0.04 & 0.05 & -0.01 \end{bmatrix},$$

According to the time scale, we define the time-varying communication delays as $\tau_i(t)(i = 0, 1, 2)$, the communication constraints is fixed to one channel $(\varrho_i = 1)$.
we presume that hydro turbine governor system accomplish the same assignment above a finite time repetitively, the length is T= 130 s.
The following two cases of actuator failure are considered in this simulation:

- Case 1: Actuator outage fault, we assume that the actuator outage fault is occurred between $110s - 115s$ with $\lambda = 0$, $\alpha = 0$.
- Case 2: Actuator suffer of struck fault, likewise, actuator struck fault occurs between with struck fault $u_k^f(t) = 2 + 1.5sin(20(t - 5))$, $\lambda = 0$, and $\alpha = 1$.

The bounds of actuator effectiveness are set as

$$\underline{\lambda} = \begin{bmatrix} 0.7 & 0 & 0 \\ 0 & 0.75 & 0 \\ 0 & 0 & 0.77 \end{bmatrix} \text{ and } \bar{\lambda} = \begin{bmatrix} 0.85 & 0 & 0 \\ 0 & 0.85 & 0 \\ 0 & 0 & 0.85 \end{bmatrix}.$$

In simulation, we are choosing the initial state of ILFD system as $x_0 = \begin{bmatrix} 0.1 & 0 & -0.1 \end{bmatrix}^T$, $\hat{\lambda}(0) = (\bar{\lambda} + \underline{\lambda})/2$, and $\hat{u}^f(0) = 0.1$;the sampling period is $T_e = 1s$.

The range of input control current of servomotor is set as $[\ 0 \quad 5mA\ ]$, the reference input speed of hydroturbine is set as $y_r(t) = 12.56rad/s$ and we let $Prob\{\beta(t) = 1\} = \beta = 0.75$.

According to Theorem 1 , we have solved the optimization algorithm in Matlab LMI toolbox, so observer gain L, fault estimator gain matrices and scalar ς can be obtained in the Table 2 and Table 3.

Table 2: Fault estimator gain matrices Λ_1, Λ_2 and observer gain L for case1.

Parameters	Matrices
Λ_1	$[\ -0.32 \quad 0.27 \quad 0.1\ ]$
Λ_2	$[\ 0.021 \quad 0.61 \quad -0.45\ ]$
L	$[\ 0.56 \quad -0.71 \quad 0.01\ ]^T$

Table 3: Fault estimator gain matrices Λ_1, Λ_2 and observer gain L for case2.

Parameters	Matrices
Λ_1	$[\ -0.3 \quad 0.28 \quad 0.1\ ]$
Λ_2	$[\ 0.035 \quad 0.60 \quad -0.43\ ]$
L	$[\ 0.66 \quad -0.63 \quad 0.21\ ]^T$

Fig. 3 and Fig 4 present the estimated fault signal and actual fault signal of actuator outage fault and struck fault at the first to sixth iterations, respectively. We can obtain that when iterative index increases, the estimating of fault achieve better result. The response curve of actuator outage fault and struck fault show that the proposed approach can track the actual signal best. It also may be observed that the fault is estimated with high precision According to Fig 2 and

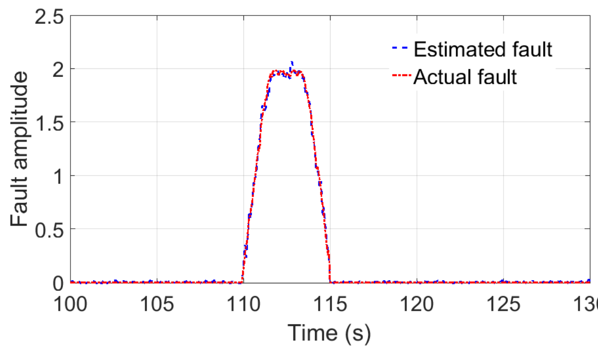

Figure 3: Actual fault and estimated fault for case 1.

Fig 5, The residual signal is increased near of actual fault with iterations growing. At third iteration, the residual signal has sufficient of convergence with the actual fault.
we can observed that of actuator outage fault and

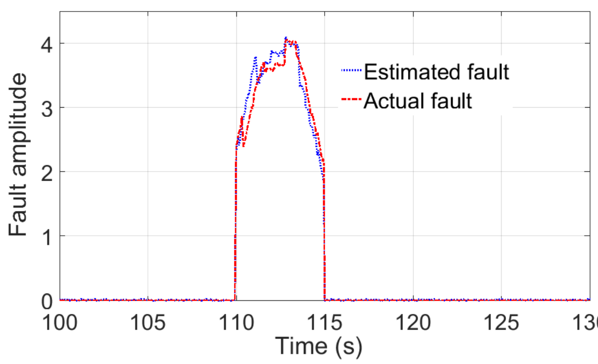

Figure 4: Actual fault and estimated fault for case 2.

struck fault are estimated with great precision. It appears that the iterative learning fault estimation observer has highly successful to estimate the actual fault.

To improve illustration of the effectiveness of

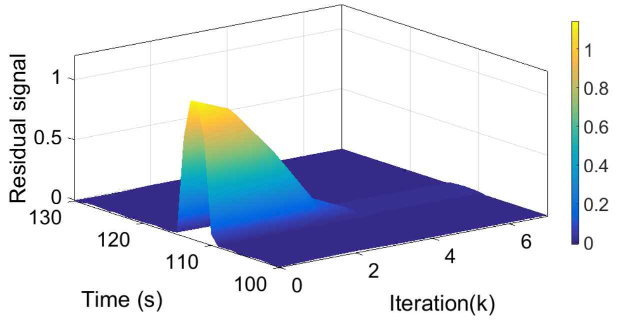

Figure 5: Residual convergence signals for case 1.

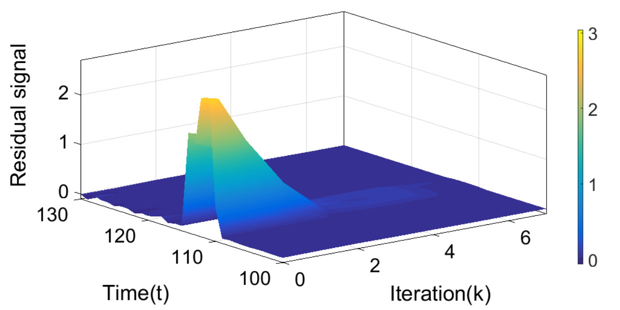

Figure 6: Residual convergence signals for case 2.

iterative learning diagnosis algorithm proposed in a class of $NCSs$ with sensor random packet losses, time-varying delays, limited communication and actuator failure , the maximum value of absolute error index ξ_k is established to assess the efficiency of fault estimation operation in different trials. The denotation of ξ_k is is defined by

$$\xi_k = \begin{array}{c} sup \left|\breve{u}_k^f(t)\right| \\ t \in [0, 300] \end{array} \tag{37}$$

Fig 3 and Fig 6 show the changes of tracking performance index (TPI) with actuator outage fault and struck fault, respectively.

In accordance with Fig 4 and Fig 6, we notice that when the iteration increases the TPI converge to zero, so we can restore the tracking accomplishment to its initial step.It is obvious that the suggested ILFD algorithm can versatility detect and estimate different actuator faults under disturbance, it will guarantee the remote control of the hydroturbine governor system better surely and effectively in actuator fault occur. .

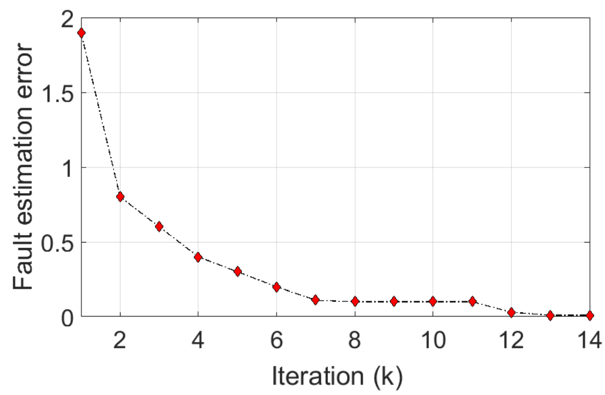

Figure 7: Tracking performance index case 1.

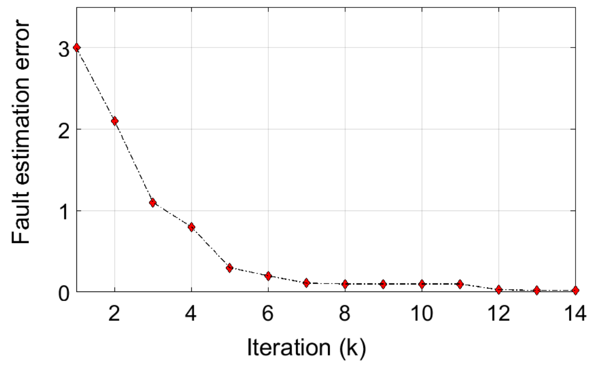

Figure 8: Tracking performance index case 2.

5 Conclusion

In this paper, a class of NCSs with random sensor-controller channels packet losses, time-varying delays, limited communication and actuator failure is investigated to design an iterative leaning fault diagnosis algorithm. Initially, corresponding fault signal is established to describe the effectiveness of information of actual fault upon process during every iteration. For designing the observer based on iterative learning fault diagnosis, virtual fault is used to estimate the corresponding actual fault through at every iteration. The asymptotic stability theory of the residual systems and the convergence conditions in terms of LMIs are applied to design iterative learning gain matrices. The dynamic of hydro turbine governor system model has been used to verify the effectiveness of the proposed algorithm based on TrueTime and Matlab/ Simulink. Also, it has been proven that the proposed algorithm may be suitable to more overall NCSs.

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